Robust fault estimation for wind turbine energy via hybrid systems.

Robust Fault Estimation For Wind Turbine Energy Via Hybrid Systems

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Abstract- The rapid development of modern wind turbine technology has led to increase demand for improving system reliability and practical concern for robust fault monitoring scheme. This paper presents the investigation of a 5MW Dynamic Wind Turbine Energy System that was designed to sustain condition monitoring and fault diagnosis with the goal of improving the reliability operations of universal practical control systems. A hybrid stochastic technique is proposed based on an augmented observer combined with eigenstructure assignment for the parameterisation and the genetic algorithm (GA) optimisation to address the attenuation of uncertainty mostly generated by disturbances. Scenarios-based are employed to explore sensor and actuator faults that have direct and indirect impacts on modern wind turbine system, based on monitoring components that are prone to malfunction. The analysis is aimed to determine the effect of concerned simulated faults from uncertainty in respect to environmental disturbances mostly challenged in real-world operations. The efficiency of the proposed approach will improve the reliability performance of wind turbine system states and diagnose uncertain faults simultaneously. The simulation outcomes illustrate the robustness of the dynamic turbine systems with a diagnostic performance to advance the practical solutions for improving reliable systems.

Keywords- Fault estimation; wind turbine; eigenstructure; genetic algorithms; optimisation; augmented robust observers

1. INTRODUCTION

The increasing advancement in modern wind power technologies as alternative source of power formation expands the concerns of component maintenance repairing. Faults diagnosis is significant for reliable continuous operations and maintenance of turbines chiefly on the remote access [1]. The unexpected changes in the monitored-system parameters could degrade the performance efficiency or decrease the availability of turbines that could increase the unhealthy system state thereby causing unplanned downtime period [2] or cause intermittent interruption during normal operations. Modern industrial wind turbine (WT) systems are becoming sophisticated and complexity in nature due to increased automation processes and technological advancements. Healthy condition monitoring and fault diagnosis are of great importance to WT operative systems that help to sustain faults prediction maintenance. Furthermore, the idea of fault diagnosis is to detect and determine faults location as well as the extent in the systems. However, the faults estimation or reconstruction extensively provides advanced information about faults that identifies the intensity of the behavior. The turbines faults can occur in various components, like the sensors or actuators parts of monitored parameters subject to normal operations. Early detection of unexpected changes from the standard working operations could save the turbine from unforeseen hazards thus improving the performance [3] and [4] is significant to the system. The obtainable information from condition monitoring can allow preventive maintenance to spontaneously help in the prediction of machine faults occurrence for the satisfactory response.

Therefore, an immense demand exists to improve online condition monitoring to allow prompt fault diagnosis, increase systems reliability and safety operation, reduce unscheduled downtime and maintenance or repair costs as well as to increase the system availability. Robust fault diagnosis has been a critical concern in fault community over the last few decades. However, system uncertainty is practically inevitable and continuously increases the chances of false alarms occurring. Based on this concern, there should be a unique approach, in distinguishing between faults and disturbances ascertain on a robust modelling solution to improve overall systems performance. The need to challenge the system robustness is to design an advanced condition monitoring and fault diagnosis to certainly monitor the behaviour of WT in the presence of disturbances. The practical applicability of fault diagnosis is quite challenging due to the presence of inevitable environmental disturbances and noises that activate the continuous request to attenuate the systems effects. Some key ideas suggest to completely get rid of uncertainty effects like disturbances on the fault indicator i.e., residuals and several methods were also, proposed to challenge this problem [4]. Furthermore, as pointed out in work regarding robust fault diagnosis suggestions was made to partially decouple uncertainty with the goal of reducing operations/maintenance costs and practically to improve the robustness of the observed systems.

It is vital to recognise that uncertainty could degrade the diagnostic performance of an ordinary fault diagnosis. The expense of wind turbine diagnoses and repairs costs can be lessened by emerging robust fault diagnosis systems [5] to improve systems. Observation is crucial in the model-based robust fault diagnosis approach, involving system input and output information to monitor the relationship between the estimated output signal and the real output system, then to analyse the outcomes. Hence, the purpose of the wind turbine robust fault monitoring yields an event of unexpected abnormality changes from the normal state and reduces the amount of false alarms and thereby improving the system performance. Observer or fault filter-based techniques have been widely employed to estimate the differences between a system's outputs and model outputs, known as the output error. These residuals are the variations between the real system's output and the observer's (monitored) output. Furthermore, the output observer describes fault detection in contrast to the state observers used for control design, which primarily estimates system states that are not measurable [6]. Several attempts have been made to improve the fault detection observer robustness for 5MW wind turbine using a hybrid stochastic approach to improving the uncertainty estimation of the system states and alarmed faults simultaneously.

Robust techniques have been investigated and reviewed to reduce the impact of uncertainties in wind turbines by the unknown input-output (UIO) observer which has received much attention in the last decades [7]-[12]. In addition, the use of optimisation methods was discussed by [13]-[18], the sliding mode and the adaptive observer [19] suggested but needs more precision to reach its convergence estimate; proportional and integral observers and descriptor are known as the augmented observers [20]-[22], the high-gain estimator [23]. At present, another critical tool for the robustness design is the linear matrix inequality (LMI) technique [24]-[26]. These methods have contributed to solving robustness problems but does not analyse satisfactory the assumptions of the practical system which set off a drawback. The application of a hybrid methodology is design for the accuracy improvement of uncertainty fault diagnosis applicable to 5MW WT discussed. The organisation of this paper is as follows: Section 2, states the model-based fault diagnosis for a 5MW wind turbine systems. Section 4 presents the design condition for the augmented observer. Section 5 discusses the methodology; with augmented observer design by Eigen structure assignment and GA optimisation. In Section 6, the simulations study results are validated and analysed with 5MW wind turbine model. Finally, the conclusion and suggestions for further work are advised in section 7.

This paper presented a hybrid methodology to promote an improved uncertainty to estimate robust fault diagnosis and analyse faults in the dynamic system. The presented approaches above can be incorporated successively to deal with wind turbine practical complications.

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2. MODEL-BASED FAULT DIAGNOSIS FOR WIND TURBINE.

Model-based robust fault diagnosis system is a key driver for online monitoring systems technology advancements to increase the performance of a 5MW WT. Faulty components of wind turbines can lead to high losses in energy production for the wind and possibly cause destruction. Therefore, the aim of robust fault monitoring is improving system reliability, robustness, stability and optimal operational performance which help to minimise power productivity losses and prevent system failures. The investigation idea is to design a robust model-based fault diagnosis system for 5MW large-capacity wind turbines [27]. The modelled types of faults mostly found in practical engineering system measured are actuator, process and sensor faults of the controlled system.

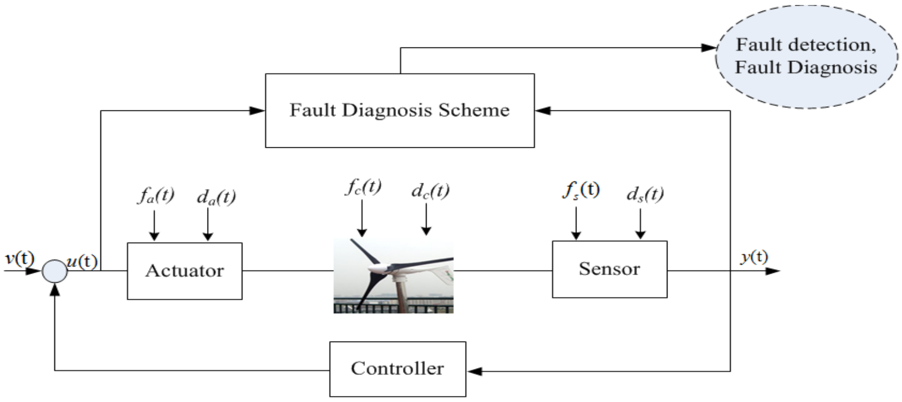


Fig. 1: Faults in a control system

Fig. 1. illustrates the schematic model of wind turbine fitted with fault diagnosis system, where $v(t)$ is the reference command, $u(t)$ is the control input with possibly uncontrolled uncertainty entry, $y(t)$ is the measured output. The symbols $d_a(t), d_c(t), d_s(t)$ are the disturbance input, component process disturbances mostly caused by modelling errors and parameter variations, and sensor disturbances. While $f_a(t)$, $f_c(t)$ and $f_s(t)$ are the actuator faults, process faults often called parameter faults and sensor faults, respectively. In this study, the focus is on actuator and sensor faults that typically occur in industrial practical processes of incipient and abrupt types of faults. The theoretical view of wind turbine model concept is systematically represented in the block

diagram as shown in Fig. 2.

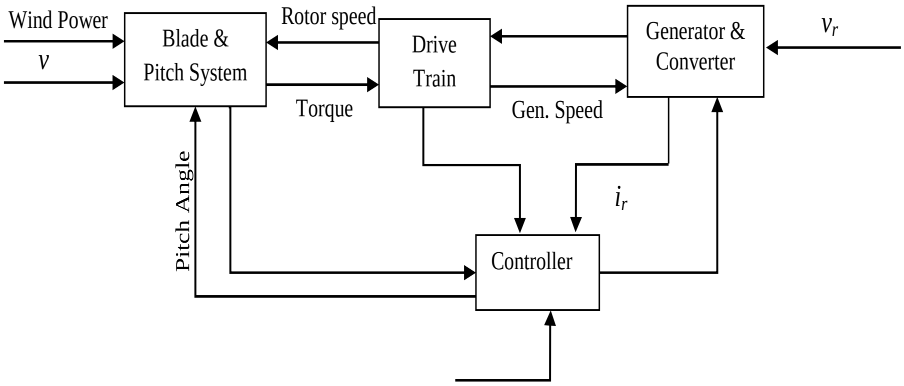


Fig. 2: 5MW wind turbine principle with rotating voltage and current of the generator

A model for a comprehensive wind energy conversion system (WECS) can be controlled with some connected subsystems. The model comprises the rotor, drive-train and the generator. Blade pitch subsystem function maintains the rotor speed in an effective wind speed changes as it converts into rotational and pitch that influence the input power. Adequate monitoring is supported for practical early fault diagnosis estimation benefits in wind turbine systems to achieve higher performance. The rotor sub block system defines the conversion of the 3D-dimensional wind speed field into aerodynamic force from the rotational movement. The drive train that assigns the aerodynamic force on the blades and pitch system to the generator, then the electrical converter subsystem describes the transformation of mechanical power at the generator into electricity. Finally, the controller is to control the output power of the turbine. Doubly-fed induction generator (DFIG) has been developed to be more suitable due to their acceptable quality of energy transfer competencies with low savings and flexible control capability. Thus, the next section describes the mathematical models of 5MW wind turbine system.

3. MODEL-BASED FAULT ESTIMATION FOR WIND TURBINE SYSTEMS

Fault estimation is a cutting-edge type of fault diagnosis approach to determine the size, shape and type of monitored faults, which can provide more information on the systems description and also, to maintain an advanced model. Tolerably, the stability quantity of a possible unexpected precise event changes plus uncertainty in the system states. Fault diagnosis represents a vital performance in the fault-tolerant control which guarantees enough information from the analysis to make a proper decision. A mathematical model of 5MW large scale dynamic wind turbine systems with a doubly-fed induction generator (DFIG) has been set up to perform condition monitoring system.

Nonlinear wind turbine dynamics is linearized to handle the designed fault diagnosis method. The mathematical description of the 5MW DFIG wind turbine was developed for simulation scope, with system corrupted faults and disturbances represented in the state-space form (1):

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + B_f f(t) + B_d d(t) \\ y(t) = Cx(t) + Du(t) + D_f f(t) + D_d d(t) \end{cases} \tag{1}$$

where $x(t) \epsilon \mathfrak{R}^n$ is the state vector, $u(t) \epsilon \mathfrak{R}^m$ is the system control input, $y(t) \epsilon \mathfrak{R}^p$ is the measurement output, A, B, C, D are known matrices of appropriate dimensions; $f(t) \in \mathfrak{R}^k$ represents the fault vector, B_f and D_f are the fault distribution matrices; $d(t) \in \mathfrak{R}^l$ is the disturbance vector, and B_d and D_d are disturbance matrices. The system parameter matrices of the wind turbine systems can be mathematically represented by equation below [25]:

$$A=\begin{bmatrix} -1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \frac{-1}{n_g} & 0 & 0 \\ 0 & \frac{K_s}{J_T} & \frac{-C_s}{J_T} & \frac{C_s}{J_T n_g} & 0 & 0 \\ 0 & \frac{K_s}{J_G n_g} & \frac{C_s}{J_G n_g} & \frac{-C_s}{J_G n_g^2} & 0 & 0 \\ 0 & 0 & 0 & -i_q & \frac{R_s}{\sigma L_r} & (\omega_s-\omega_m) \\ 0 & 0 & 0 & \frac{i_d+L_m u_{sq}}{L_s\omega_s} & -(\omega_s-\omega_m) & \frac{R_r}{\sigma L_r} \end{bmatrix} B=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{1}{J_T} & 0 & 0 & 0 \\ 0 & 0 & \frac{-1}{J_G} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$C=\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{-\sqrt{3}n_p L_m V_s K_c}{\sigma L_r L_s \omega_s} \end{bmatrix} \quad D=\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \text{ where } K_c=0.8383. \tag{2}$$

The symbols of the 5MW wind turbine model are defined in Table 1, below [15], where the wind turbine is operating at a wind speed of 10 m/s.

The states x, inputs u and output y of the wind turbine model are defined as:

$$x=\begin{bmatrix} \beta \\ \theta_K \\ \omega_{wt} \\ \omega_{m,} \\ i_{dr} \\ i_{qr} \end{bmatrix}=\begin{bmatrix} \text{pitch angle} \\ \text{angular speed position} \\ \text{wind turbine speed} \\ \text{generator speed} \\ \text{d - axis rotor current} \\ \text{q - axis rotor current} \end{bmatrix} \quad \text{The entire system state}$$

$$u=\begin{bmatrix} \beta_d \\ T_{wt,} \\ T_e^c \\ v_{dr} \\ v_{qr} \end{bmatrix}=\begin{bmatrix} \text{pitch angle} \\ \text{wind turbine torque} \\ \text{electrical control torque} \\ \text{active control rotor voltages} \\ \text{reactive control rotor voltages} \end{bmatrix} \quad \text{Predictive or known input value of the Wind turbine}$$

$$y=\begin{bmatrix} \beta \\ \omega_{wt} \\ \omega_m \\ T_e \end{bmatrix}=\begin{bmatrix} \text{pitch angle} \\ \text{wind turbine speed} \\ \text{generator speed} \\ \text{electromagnetic torque} \end{bmatrix} \quad \text{Wind turbine output}$$

In this study, the trade-off between uncertainty and faults could be challenging to distinguish the influences of faults from the consequences. Therefore, it is desirable to reduce the influence of disturbances by optimization the systems estimation error. Environmental disturbances could certainly reduce the performance of fault diagnosis system that could mostly act as a cause of false and missed alarms. So, robustness is important to minimizing the influence of unknown disturbances instead of wholly or partially decoupling the disturbances from the system. Therefore, the considered fault f, in a real-world design is assumed to be surrounded with obvious uncontrollable and inevitable environmental uncertainties i.e., the second derivative of fault $\ddot{f}$ is assumed to be bounded [10] in engineering practical systems [21] and [23].

$$\ddot{f}(t) \neq 0 \tag{3}$$

Let the augmented state vector be termed as (4),

$$\overline{x}=\left[x^T \ \dot{f}^T \ f^T\right]^T \in \Re^{\overline{n}} \tag{4}$$

The model in (1) can be re-constructed in an augmented state space form as follows:

$$\begin{cases}\dot{\bar{x}}(t) = \bar{A}\bar{x}(t) + \bar{B}u(t) + \bar{B}_d d(t) + \bar{G}\ddot{f}(t) \\ y(t) = \bar{C}\bar{x}(t) + Du(t) + D_d d(t)\end{cases} \tag{5}$$

$$\text{where, } \bar{x} = \begin{bmatrix} x \\ \dot{f} \\ f \end{bmatrix}, \bar{A} = \begin{bmatrix} A & 0 & B_f \\ 0 & 0 & 0 \\ 0 & I & 0 \end{bmatrix}, \ \bar{B} = \begin{bmatrix} B \\ 0 \\ 0 \end{bmatrix}, \bar{B}_d = \begin{bmatrix} B_d \\ 0 \\ 0 \end{bmatrix}, \ \bar{G} = \begin{bmatrix} 0 \\ I \\ 0 \end{bmatrix}, \ \bar{C} = \begin{bmatrix} C & 0 & D_f \end{bmatrix}. \tag{6}$$

The wind turbine model is linearized to simplify the system composition design. The augmented fault observer is design based on the linear model of the system. The augmented observer has a supplementary augmented gain $\bar{K}$, that continuously corrects the system output and advances the state estimates which can be constructed as follows:

$$\dot{\hat{\bar{x}}}(t) = \bar{A}\hat{\bar{x}}(t) + \bar{B}u(t) + \bar{K}(y(t) - Du(t) - \bar{C}\hat{\bar{x}}(t)) \tag{7}$$

where $\hat{\bar{x}}(t)\epsilon\Re^{\bar{n}}$ is the estimate of the augmented state vector $\bar{x}(t)\epsilon\Re^{\bar{n}}$; and $\bar{K}\epsilon\Re^{\bar{n}\times p}$ is the augmented observer gain to be designed. The augmented observer signal is to estimate the states and the faults of wind turbine system simultaneously.
Let the estimation error be,

$$\bar{e}(t) = \bar{x}(t) - \hat{\bar{x}}(t), \tag{8}$$

Exploring the difference between the real system and the estimated state in (5) and (7), the estimation error dynamics is governed by the following equation:

$$\dot{\bar{e}}(t) = (\bar{A} - \bar{K}\bar{C})\bar{e}(t) + (\bar{B}_d - \bar{K}D_d)d(t) + \bar{G}\ddot{f}(t) \tag{9}$$

The transfer function of (9) can be given as follows:

$$e(s) = (sI - \bar{A} + \bar{K}\bar{C})^{-1}(B_d - \bar{K}D_d)d(s) + (sI - \bar{A} + \bar{K}\bar{C})^{-1}\bar{G}(s^2 f(s)) \tag{10}$$

As a result, the proposed goal is to design an augmented observer gain $\bar{K}$ to make (10) asymptotically stable when $d(t) = 0$; and the estimation error to be as small as possible, when disturbance is presence, $d(t) \neq 0$.
Generally, the augmented observer also refer to as filter plays a key role in model-based fault diagnosis methods, which uses the information from the input and output to monitor the regularity between the expected and the actual output process of the system. Also, to amplify and gives more analysis diagnosis information results comparatively to the ordinary observer.
Hence, to attenuate the effects from the uncertainties, the methodology here uses optimization designs to make the estimation error robust against the uncertainties like disturbances [15]. The proposed methodology for robust fault diagnosis of wind turbine systems involves: Augmented observer, eigenstructure assignment and Genetic algorithm (GA) optimization. The hybrid design criteria and process will be discussed in the next sections.

4. DESIGN CONDITION FOR THE AUGMENTED OBSERVER

In order to make $(\bar{A} - \bar{K}\bar{C})$ internally stable, this sufficient condition of the pair $(\bar{A}, \bar{C})$ must be observable (or measurable), a clear sufficient condition must be reached. The existence outline for fault estimator in (11)-(12) expressed the strict condition that needs to be met.

Theorem 1
If,

$$\bar{n} = n + 2k = \text{rank}\begin{bmatrix} sI - \bar{A} \\ \bar{C} \end{bmatrix} \tag{11}$$

And for any complex s (or unstable complex s).

$$= \begin{cases} rank\begin{bmatrix} sI - A \\ C \end{bmatrix} + 2k, & s \neq 0, \\ rank\begin{bmatrix} A & B_f \\ C & D_f \end{bmatrix} + k, & s = 0. \end{cases}$$

Proof

From the condition (11), one can get the equivalent source where the pair $(\bar{A}, \ \bar{C})$ is observable is follows:

Theorem 2

$$rank\begin{bmatrix} A & R_1 \\ C & D_f \end{bmatrix} = n + k \tag{12}$$

$$Leading \text{ to } rank\begin{bmatrix} sI - \bar{A} \\ \bar{C} \end{bmatrix} = \bar{n}. \tag{13}$$

Therefore, the design goal is to design an observer gain matrices $\overline{K}$ to attenuate disturbance $d(t)$ effects i.e., for the fault estimation to have good robustness against disturbances. If an effective observer (7) can be designed, the augmented estimate leading to the parallel generation of states and faults as follows:

$$\begin{cases} \hat{f}(t) = [0_{k\times\bar{n}} \quad 0_{k\times k} \quad I_{k\times k}]\hat{\bar{x}}(t) \\ \hat{x}(t) = [I_{\bar{n}\times\bar{n}} \quad 0_{\bar{n}\times k} \quad 0_{\bar{n}\times k}]\hat{\bar{x}}(t) \end{cases} \tag{14}$$

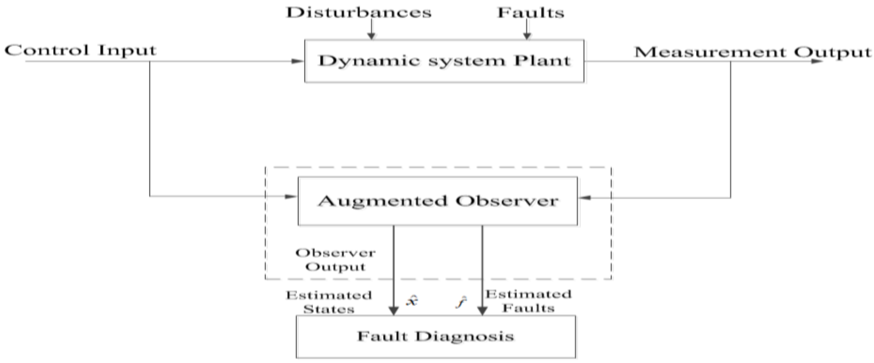


Fig 3. Conceptual structure of robust model-based augmented observer

Various optimization techniques were utilized for robust fault detection [4]-[7]. In this study, GA optimization and augmented system approach are integrated for robust fault estimation in induction motors.

5. AUGMENTED OBSERVER DESIGN BY BY EIGEN STRUCTURE ASSIGNMENT AND GA OPTIMISATION

5.1 Eigenstructure Assignment

Eigenstructure is employed for seeking an optimal observer gain parameterisation of the elements to specify in predefined points or regions according to needed augmented observer responses. The eigenvalues of the observer can be real numbers or complex-conjugate and could be either. Assume that there are $\bar{n}_r$ real eigenvalues λ_i $(\mathrm{i} = 1,2,\cdots,\bar{n}_r)$ and $\bar{n}_c$ pairs of complex-conjugate eigenvalues $\lambda_{j,re} \pm j\lambda_{j,im}$ $(j = 1,2,\cdots,\bar{n}_c)$, any of $\bar{n}_r$ and $\bar{n}_c$ to satisfy the following relation:

$$\overline{n}_r + 2\overline{n}_c = \overline{n} \tag{15}$$

The relationship between the eigenvalues and eigenvectors of the closed observer matrix $(\bar{A} - \overline{K}\bar{C})$ can be expressed as:

$$(\bar{A} - \overline{K}\bar{C})v_i = \lambda_i v_i \tag{16}$$

where λ_i is the eigenvalues of the closed-loop observer matrix $(\bar{A} - \overline{K}\bar{C})$, and v_i are the corresponding eigenvectors of λ_i, and let $i = (1,2,3, \ldots \bar{n})$. The equation (16) can be rewritten as:

$$(\bar{A} - \lambda_i I)v_i = \overline{K}\bar{C}v_i \tag{17}$$

$$l_i = [\bar{C}(\bar{A} - \lambda_i I)^{-1}]^T v_i \tag{18}$$

$$L = [l_1^T, l_2^T \ldots\ldots, l_{\bar{n}}^T] \tag{19}$$

$$V = [v_1^T, v_2^T \ldots\ldots, v_{\bar{n}}^T] \tag{20}$$

Therefore, the optimization of $\overline{K}$ has been transformed to seek the optimal parameters of λ_i and v_i elements. Hence, the augmented observer gain can be expressed as

$$\overline{K} = (L^{-1})V \tag{21}$$

5.2 The Cost Function

The transfer function (10) represent the physical purpose of the error that clearly states the problem that needs to be solved based on the unseparated environmental disturbance and interrupted faults that could corrupt the normal healthy operation of the dynamic systems. The optimized system could definitely improve the robustness of fault diagnosis against disturbances, which will contribute to the practical robustness solution of fault diagnosis or fault estimation algorithm.
The key performance indicator for physical measurement and to attenuate its influences from the disturbances and concerned faults are introduced in the cost functions also, known as performance indices. Thereby minimizing $\bar{K}$ will have an improve disturbance attenuation performance. Also, to ensure the estimation error dynamics of (11) to be asymptotically stable and satisfy the robust performance index below useful for the augmented observer design. Hence, the cost function to be evaluated is given as follows:

$$\text{Minimize } T = T_1 + T_2, \qquad \text{Simply attenuate } T(\overline{K}) \tag{22}$$

where,

$$T_1 = \|(sI - \bar{A} + \bar{K}\bar{C})^{-1}(B_d - \bar{K}D_d)\|_{s=j\omega_d} \tag{23}$$

$$T_2 = \|(sI - \bar{A} + \bar{K}\bar{C})^{-1}\bar{G}\|_{s=j\omega_f} \tag{24}$$

Based on the analysis above in (10), two robust performance indices are proposed as follows.

$$\begin{cases} \text{minimize } T_1 = \|H_d(s)\|_{s=j\omega_d} \\ \text{minimize } T_2 = \left\|H_f(s)\right\|_{s=j\omega_f} \end{cases} \tag{25}$$

where ω_d is the dominant frequency of the disturbance, and the frequency of the second order derivative $\ddot{f}$ expected for a typical engineering practical systems is considered to be low according to the assumption from spectrum analysis. In order to minimise the influences from the disturbance d, the observer gain $\overline{K}$ should meet the following performance index after incorporating the disturbance frequency information. Therefore the cost function in (22) is the complex basic concern that requires the performance index to be minimize.

5.3 Genetic Algorithm Optimization

GA is an evolutionary optimization algorithm, to optimize the observer design which can be probability solved by *gatool* solver in MATLAB [14] as shown in Fig. 4 below. In this paper, the GA design procedure of the fault estimator for wind turbine system is summarised as follows:

Design Procedure for GA-based fault estimator
The exploratory design procedure of seeking optimal $\overline{K}$ can be outlined as follows.

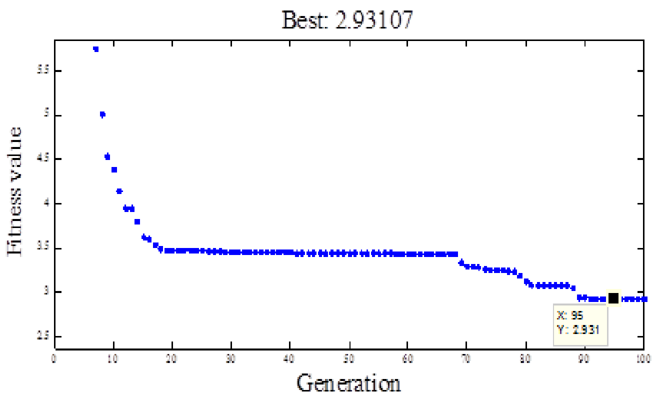
- **Check the observer condition:** Check whether (11) and (13) are satisfied. If yes, go to the next step; otherwise, stop the procedure.
- **Set the parameters to be optimized:** The total number of the parameters to be optimized is calculated as $\bar{n} + \bar{n} \times p$, to set the parameters.
- **Fitness Evaluation:** The fitness function is defined in (21).
- **Constrains:** The eigenvalues $(\bar{A} - \overline{K}\bar{C})$ are bounded to be stable.
- **Selection:** Random search is piloted to many regions, rather than a single region, with fast convergence, in order to search the area of concern effectively for a global result.
- **Reproduction:** The algorithm selects the individual parameters that have better fitness values as parents to breed children at each fresh generation to make random changes in the individual population.
- **Stop:** The global minimum point is reached, where the stopping conditions determine the end of the algorithm is terminated when the number of generations exceeded, otherwise return to ***FITNESS FUNCTION*** to continue the evolution.
- **GA running:** Run GA until any of the stop criteria is met.

6. SIMULATION STUDY FOR WIND TURBINE SYSTEM

The robust fault detection system is designed and optimise to be most sensitive to system faults and to attenuate the estimation error to have good robustness against the system. The methodology depends on designing an augmented observer by a combined model as stated above. The nonlinear 5MW wind turbine model was linearized by Taylor approximation to design a linear equivalence in small signal principles and determine the state model in Simulink/Matlab as demonstrated below.

A. Fault estimation for multiple sensor faults

It is assumed that the first three sensor faults occur successively. In this simulation studies, the dominant disturbance is assumed to be defined as: $d(t) = 0.001\sin(12\pi t)$. The GA evolutional final optimal process can be displayed as the best iteration below (Fig.4). The optimal GA-based observer gain matrix sensor fault is calculated and verified as follows [28]:



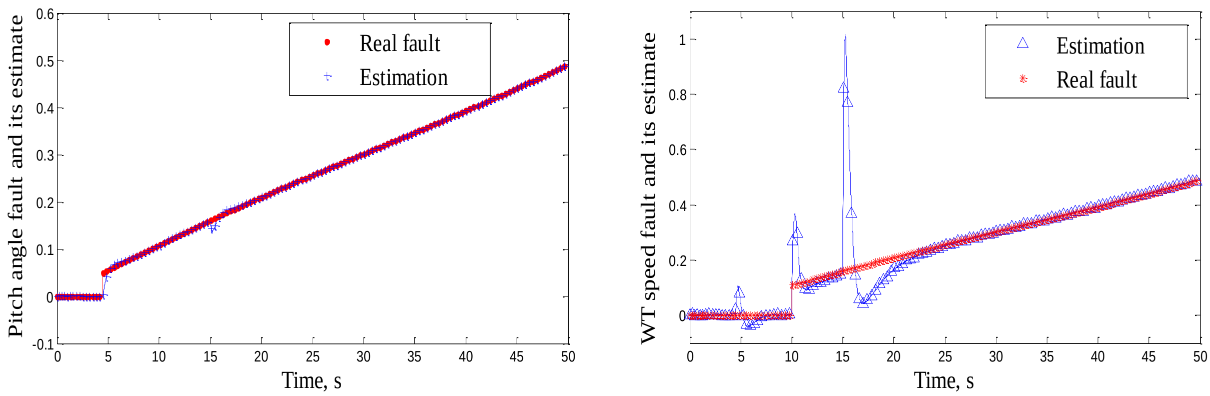
$$\bar{K}_{GA} = \begin{bmatrix} -0.0037 & -0.0053 & 0.0071 & 0.0001 \\ -17.3390 & -26.8135 & -31.3327 & 0.3679 \\ -26.3733 & -32.7155 & -64.0829 & 0.2484 \\ -0.0283 & -0.0487 & -0.0720 & 0.0007 \\ -3.0730 & -6.5951 & -16.9141 & -60.2632 \\ 39.6491 & 247.8310 & 146.4340 & -5.1615 \\ 1.8789 & -0.8540 & -3.6742 & 0.0015 \\ -1.4823 & 3.1287 & -2.8359 & -0.0005 \\ 3.1459 & 1.5077 & 8.3643 & -0.0040 \\ 3.0748 & -0.4325 & -1.7292 & 0.0004 \\ 25.3790 & 36.4629 & 62.3357 & -0.2486 \\ 2.2416 & 1.1250 & 7.5367 & -0.0018 \end{bmatrix} \quad (26)$$

Fig. 4. The best sensor output plot of GA evolutional method.

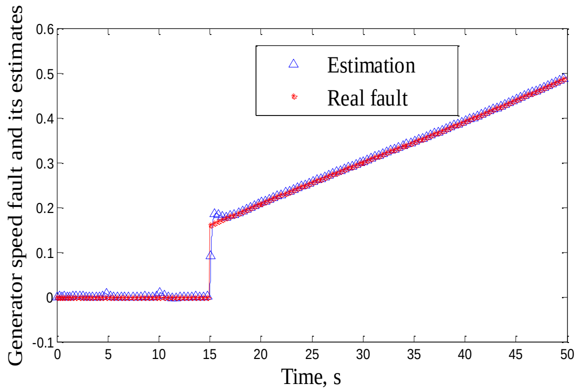
A1) Incipient sensor faults:

Wind turbines operate at a low-frequency sensitivity of fault performance index set to be maximized and the robustness disturbance frequency information is designed to attenuate the disturbance to its minimal. Fig. 5 demonstrates the wind turbine parameters as stated in each curve displayed in the figure below with sensor faults with their estimations respectively, where the “red line” views the real fault signals, and the “blue line” signifies estimation. The proposed observer gain is calculated and optimized by GA with excellent estimation performance for abrupt and incipient faults are the two engineering-oriented systems in industrial processes and system states.

The estimates of the three sensor faults defined as D_f and the actuator considered as fault-free in this scenario as represented in Fig. 5, which has shown that fault estimation has detected the three sensor faults in the types of ramp signals are estimated excellently.



(a) The pitch angle and its fault estimation. (b) The Wind turbine speed and its fault estimation.



(c) The generator speed and its estimate

The first to three sensor faults are defined to be as follows:

$$f_{s1.Ramp} = \begin{cases} 0.01t + 0.001sin(0.1t), & t \geq 4.5s \\ 0, & t < 4.5s \end{cases} \quad (27)$$

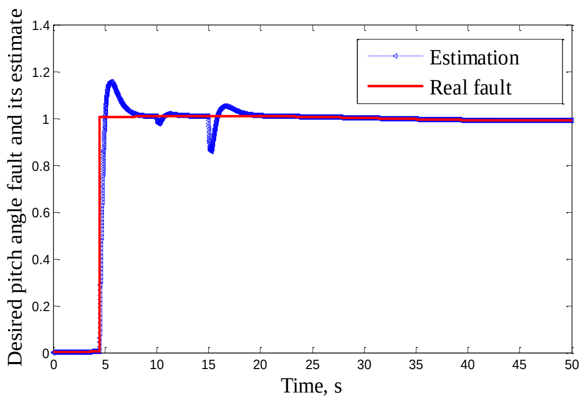
$$f_{s2.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \quad (28)$$

$$f_{s3.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 15s \\ 0, & t < 15s \end{cases} \quad (29)$$

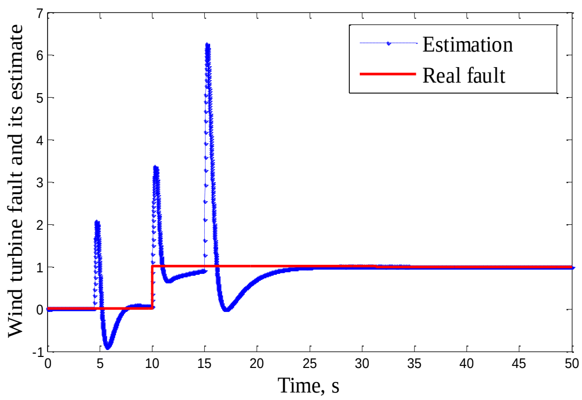
Fig. 5. The incipient sensor faults and their estimate

B1) The Abrupt sensor faults

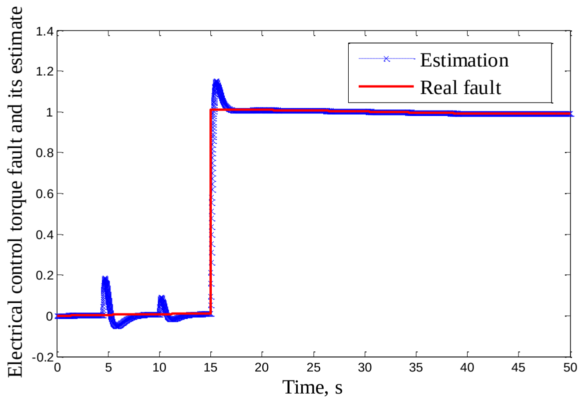
The simulation results in Fig. 6. shows an excellent tracking performance for the proposed schemes, the convergence curves exhibit the estimation performance for the actuator faults respectively.



(a) The pitch angle fault and its estimate



(b) The wind turbine fault and its estimate



(c) The generator speed and its estimate

The first three sensor faults are assumed to be as follows:

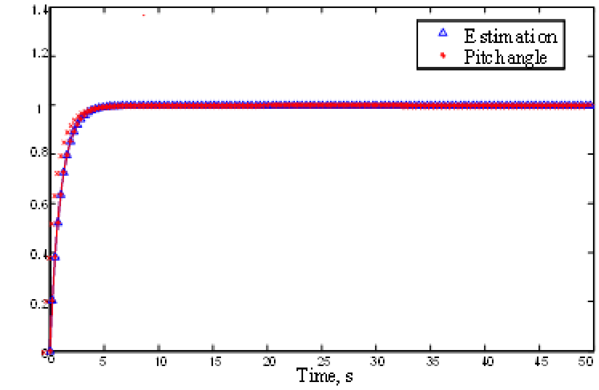
$$f_{s1.step} = \begin{cases} 1 + 0.001sin(0.1t), & t \geq 4.5s \\ 0, & t < 4.5s \end{cases} \quad (30)$$

$$f_{s2.Step} = \begin{cases} 1 + 0.001\sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \quad (31)$$

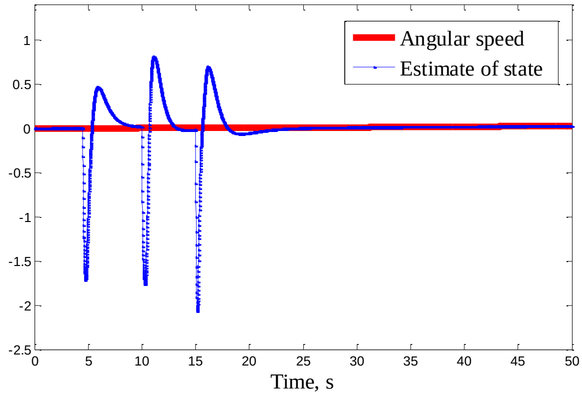
$$f_{s3.step} = \begin{cases} 1 + 0.001\sin(0.1t), & t \geq 15s \\ 0, & t < 15s \end{cases} \quad (32)$$

Fig. 6. The abrupt (step) sensor faults and its estimate

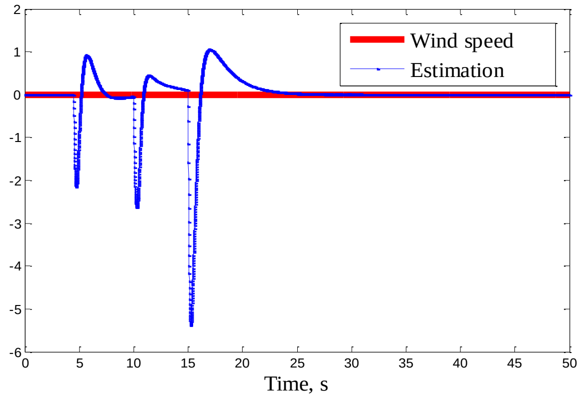
As the by-product, the estimates of the system states are also obtained, which are depicted in Fig. 7. One can see the six states have been well estimated. The estimate of the system states has been achieved with available information from the systems input and output of the WT model.



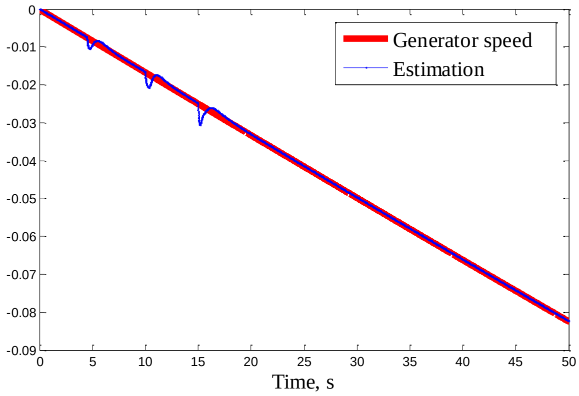
(a) The pitch state and its estimates



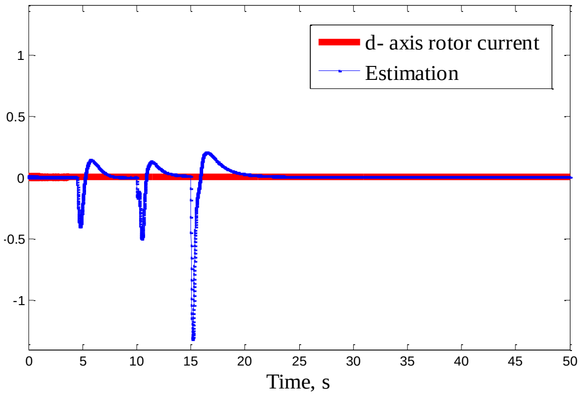
(b) The angular speed position state and its estimate



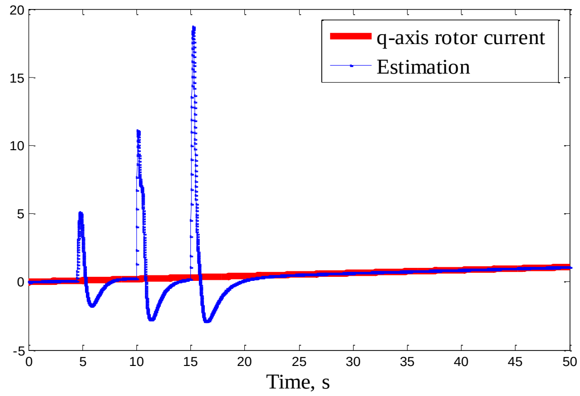
(c) The wind speed state and its estimate



(d) Generator speed state and its estimate



(e) d-axis rotor current state and its estimate



(f) q-axis rotor current and its estimate

Fig. 7. States x_{i-n} and its estimate

B. *Fault estimation for multiple Actuator faults*

It is assumed to have three actuator faults, which occur sequentially. By using the defined algorithm above, the fitness value evolution curve is illustrated in Fig. 8. The actuator optimal observer gain reached by GA is shown below [28]:

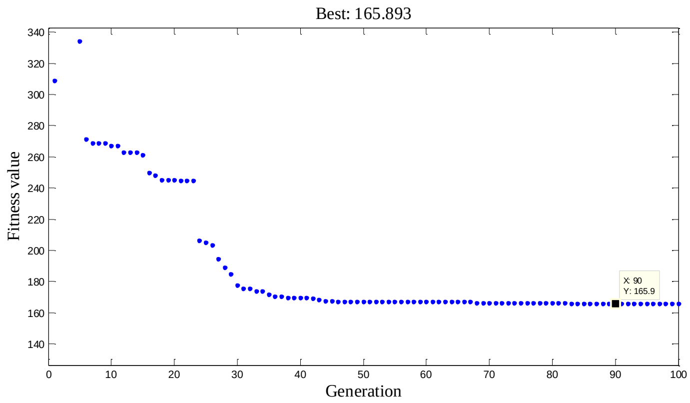


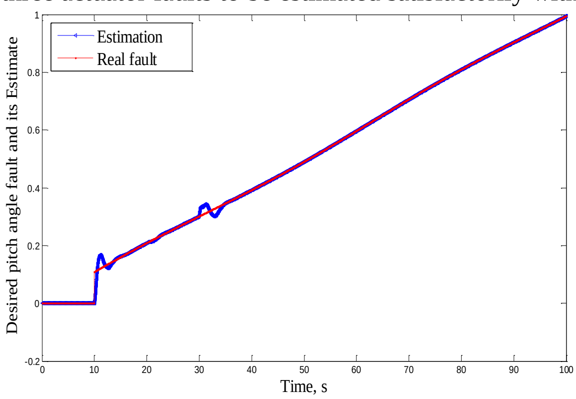
Fig. 8. The fitness evolution by GA algorithm

$$\bar{K}_{GA} = \begin{bmatrix} 6.2288 & 1.6312 & -23.9501 & -0.0110 \\ 180.0053 & 56.8155 & -599.0632 & 0.2679 \\ 0.2264 & 5.8281 & 25.1646 & 0.0162 \\ 0.1156 & 0.0075 & -0.2835 & 0.0004 \\ 32.9596 & -9.7649 & 49.6414 & -60.2155 \\ -604.0544 & -689.3634 & 314.2205 & -4.8630 \\ 10.5965 & 4.6452 & -56.7652 & -0.0215 \\ 74.1747 & 40.5367 & -148.6501 & 0.2521 \\ 1.0190 & 7.2841 & 68.3764 & 0.0561 \\ 15.5997 & 5.4915 & -72.2895 & -0.0308 \\ 208.4218 & 95.1749 & -572.2227 & 0.4945 \\ 0.9594 & 11.2842 & 84.8977 & 0.0609 \end{bmatrix}$$

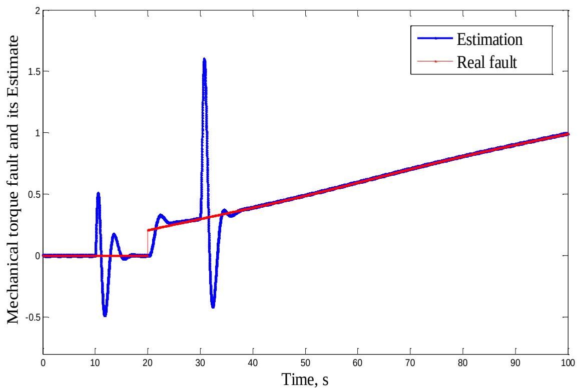
The capacity of the proposed global optimum augmented observer or fault estimator is modelled which shows a great improvement in fault diagnosis technology to the comprehensive information revealed during the analysis.

A2) Actuator Incipient fault and its Estimate

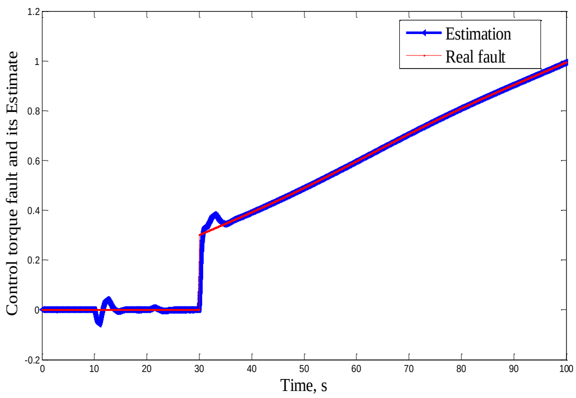
The proposed augmented optimisation method approves the robust actuator fault diagnosis via abrupt and incipient typical type of practical faults practices, considered for this simulation purposes. The disturbance is defined as $d(t) = 0.001\sin(12\pi t)$ corrupted by faults as stated in (33)-(35). The actuator faults matrix are represented as $B_f = B$ for actuator fault, $D_f = 0$ indicates, output sensors to be fault-free. Fig. 9, has shown the three actuator faults to be estimated satisfactorily with disturbance influences minimized.



(a) Desired pitch angle and its estimate



(b) Mechanical torque and its estimate



(c) Control torque fault and its estimate

The first three actuator faults are assumed to be as follows:

$$f_{a1.Ramp} = \begin{cases} 0.01t + 0.001sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \quad (33)$$

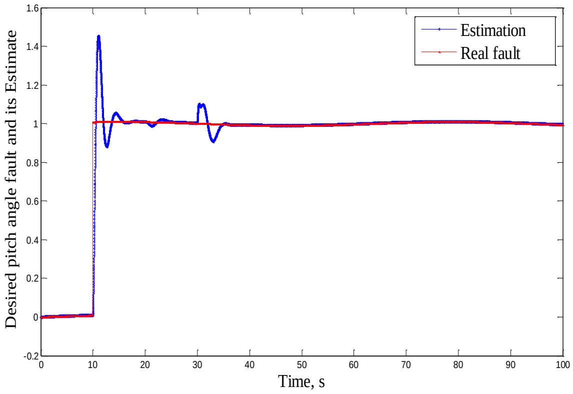
$$f_{a2.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 20s \\ 0, & t < 20s \end{cases} \quad (34)$$

$$f_{a3.Ramp} = \begin{cases} 0.01t + 0.001\sin(0.1t), & t \geq 30s \\ 0, & t < 30s \end{cases} \quad (35)$$

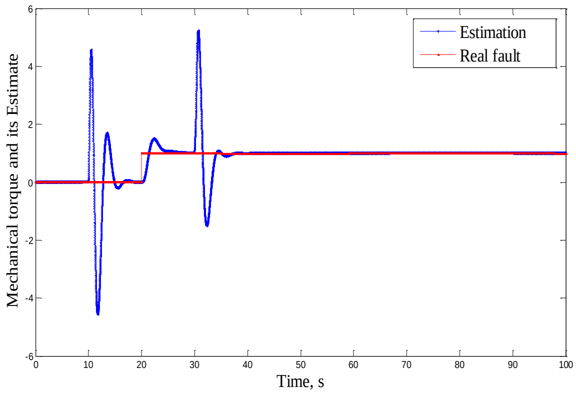
Fig. 9. Wind turbine actuator incipient faults and its estimate.

In this case, we aim to concentrate on the real fault and its estimate for actuator faults

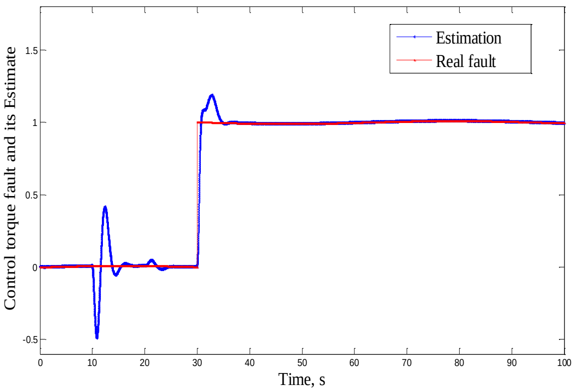
A2) Abrupt actuator faults and its Estimate



(a) Desired pitch angle actuator fault and its estimate



(b) Mechanical torque actuator fault and its estimate



(c) Control torque actuator fault and its estimate

The first three actuator faults are assumed as follows.

$$f_{a1.step} = \begin{cases} 1 + 0.01sin(0.1t), & t \geq 10s \\ 0, & t < 10s \end{cases} \tag{36}$$

$$f_{a2.step} = \begin{cases} 1 + 0.01\sin(0.1t), & t \geq 20s \\ 0, & t < 20s \end{cases} \tag{37}$$

$$f_{a3.step} = \begin{cases} 1 + 0.01\sin(0.1t), & t \geq 30s \\ 0, & t < 30s \end{cases} \tag{38}$$

Fig. 10. Step actuator faults and its estimate: Wind turbine system

As illustrated in Fig. 10. which shows an excellent estimation tracking performance for the abrupt actuator faults displaying the real concerned faults and its estimation with minimized disturbances.

The above simulated figures demonstrated both the concerned faults and the system states that ascertained the unique proposed method that practically shows the distinction solutions. For the system, both actuator and sensor faults were robustly estimated together with the concerned faults and system states displaying quick clear responses with an appropriate convergence quality and successful attenuation. This technique seeks an optimal augmented observer gain which minimizes the disturbances influences and the non-dominant fault components. The effective robust fault diagnosis has got lots of advantages to the wind turbine operations and maintenance in terms of saving costs and improving the reliability capacity of the turbine systems.

7. CONCLUSION

In this paper, a hybrid methodology has robustly diagnosed industrial practices faults and estimates the system states was developed to handle systems subjected to process disturbances and corrupted by faults. The robust model-based fault diagnosis was designed for 5MW large-scale wind turbine systems to analyse the controlled behaviour in the presence of faults and connected uncertainty. The addressed combined robustness method was evaluated and analysed as a cutting-edge contributing more information in regards to the disturbances attenuation of stochastic linear systems which can also be directly applied to nonlinear systems. The two practical types of concerned faults in engineering practices were considered, reconstructed and the performance as well the effectiveness of robust fault diagnosis techniques were demonstrated with the scenarios-based design. The methodology diagnosed with excellent performance prediction of the system faults and estimated matching system states. The economic mission impact would be beneficial to saving repairs costs, improving efficiency, reliability and reducing the number of fast respond emergencies in the modern industries with clear distinguishing between the real faults and uncertainty. Therefore, the combined robust estimation of fault diagnosis gives more analysis information about the investigated systems which offer to handle various practical industrial systems compared to other fault detection and diagnosis tools.

The simulation studies have demonstrated good performance for the proposed method that analysed the alarmed faults with the presence of uncertainty. It can be anticipated and proven that better disturbance attenuation represents an excellent tracking performance of immediate faults detection and system states estimation. The finality may be considered with real industrial data collected during healthy operations of wind turbines however, the modelling error can be address. Further study could investigate more advanced approaches with fault tolerant combination to enhance and developed robust fault estimation for better improves performance.

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